Universidad de los Andes | HUMAN DEVELOPMENT LAB

WORKING PAPER N°2024011

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Published by
Human Development Lab.
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Las Condes.
Santiago, Chile

Last update: October 29, 2023.

This working paper was produced as part of the Development in Higher Education Initiative of the Human Development Lab and was first published on October 29, 2023. The Human Development Lab is funded by Universidad de los Andes, Chile.

Direct and Indirect Effects of Affirmative Action in University Admissions†

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October 29, 2023
Latest Version

Abstract

This paper provides causal evidence that giving preferential access to college to talented students from disadvantaged backgrounds not only benefits them but also their younger siblings and neighbors. We study a program that reserves places for students completing high school in the top 10% of their class. We thus overcome endogeneity concerns using a regression discontinuity design through which we compare the outcomes of individuals whose high school GPA places them marginally above and below of the top 10% of their class. We proceed in a similar way to estimate indirect effects, as we compare individuals with an older sibling or neighbor near the eligibility threshold for preferential admissions. Eligibility for preferential admissions increases four-year college enrollment by 4 (9%) percentage points and college completion by 1.8 (5%) percentage points. The younger siblings and close neighbors of direct beneficiaries also benefit from the program. They become around 2 percentage points more likely to attend and to complete a four-year college degree. Social spillovers of programs that expand access to college are not trivial and should be incorporated in the evaluation and design of this type of program.

JEL codes: *I21, I23, I24, I28*
Keywords: *affirmative action, university access, social spillovers*

† For granting us access to the administrative data we use in this project, we thank the Chilean Ministry of Education and DEMRE. We also thank the financial support of the Fondecyt Iniciación Project 11230169 and of the Spencer Foundation Grant 10039719. Gustavo Faúndez provided excellent research assistance. Supplemental materials are available in the Online Appendix.

1 Introduction

Students from disadvantaged backgrounds are significantly less likely to attend higher education and selective colleges than more affluent students. These differences persist even when generous funding is available and when focusing on talented students who would likely benefit from attending college (Hoxby and Avery, 2013; Altmejd et al., 2023). This phenomenon is not only costly for individuals. At the aggregate level, it can impact economic growth and inequality (Goldin and Katz, 2008). To tackle some of this inequality and incorporate talented individuals from underrepresented groups into higher education, many countries have introduced affirmative action programs in college admissions. While these programs are ubiquitous—i.e., one-quarter of the world's countries have some form of affirmative action in college admissions (Jenkins and Moses, 2014)—they are still highly controversial on the grounds of fairness.[1] The effectiveness and efficiency of these programs are also highly debated (see Arcidiacono and Lovenheim, 2016, for a discussion of this literature). Despite growing evidence documenting large social spillovers in the higher education trajectories of individuals—see for instance Barrios-Fernández (2022); Altmejd et al. (2022)—indirect beneficiaries of affirmative action programs have been absent from this debate.

This paper combines detailed educational records from Chile with a regression discontinuity design (RDD) to provide causal evidence that affirmative action in college admissions not only improves the trajectories of the students directly benefiting from preferential access to college, but also the trajectories of some of their close peers (e.g., siblings and neighbors).

We study an affirmative action program—i.e., *Beca de Excelencia Académica* (BEA)—that reserves places in selective universities for students graduating from subsidized high schools in the top 10% of their class.[2] In contrast to the percentage admission plans of California, Florida, and Texas, students eligible for the BEA are not guaranteed a place in college. Nevertheless, the BEA increases their admission probabilities as it offers an additional path into college for them. These students still have to take the national college

[1] For instance, on June 29, the US Supreme Court voted in a 6-3 decision to curb affirmative action in higher education—ending a four-decade precedent that allowed colleges and universities to broadly consider applicants' race in their admissions processes. The decision spurred a heated debate among the public.

[2] When the BEA was introduced in 2007, it targeted students graduating in the top 5% of their class. It was expanded to students graduating in the top 7.5% of their class in 2013 and to students graduating in the top 10% of their class in 2014.

admission exam, but now they can compete for regular places and for BEA reserved places.

To estimate the causal effect of BEA on students' trajectories, we exploit the cutoff rule that determines eligibility for the program. We use data on the universe of high school graduates from 2006 to 2021 and recover the GPA rank of each student. This allows us to build high-school-year-specific eligibility cutoffs and use an RDD to compare students marginally above and marginally below the eligibility cutoff of their high school. We proceed in a similar way to study the effects of BEA on the younger siblings and close neighbors of its direct beneficiaries. To estimate these indirect effects, instead of comparing students near the BEA-eligibility cutoff, we compare the outcomes of their peers.

We find economically significant effects of BEA eligibility on both its direct beneficiaries and their close peers.

Students marginally qualifying for BEA become 3.4 percentage points (5%) more likely to enroll in higher education and 4.3 percentage points (9%) more likely to enroll in a 4-year college. They also become more likely to enroll in a degree in the top 25% of selectivity—measured by the scores of admitted students in the national admission exam—and in the top 25% of expected earnings—measured by the average earnings of former students four years after graduation. Thus, on top of increasing the representation of disadvantaged students in higher education, BEA eligibility increases their representation in prestigious programs. Importantly, the increase we find in enrollment also translates into an increase in college completion. Students marginally eligible for BEA also become more likely to graduate from a 4-year college, from a selective degree, and from a degree associated with high earnings.

We also find evidence of large spillovers on younger siblings and close neighbors of students eligible for BEA. Indeed, having an older sibling or a close neighbor marginally eligible for BEA increases enrollment in 4-year colleges by 2.0 and 2.3 percentage points, respectively. In addition, it increases 4-year college graduation probabilities by a similar amount, suggesting that being close to a direct beneficiary of BEA is actually beneficial.

Finally, we show that the increase that close peers of direct BEA beneficiaries experience in college enrollment and graduation does not seem to be driven by an improvement on their academic performance, but rather by an increase in the probability of applying to higher education. Younger siblings and close neighbors of students eligible for BEA do not improve their high school grades or their scores in the college admission exam. We do, however, find some suggestive evidence that they become more likely to apply to university.

Interestingly, we find that neighbor spillovers rapidly decline with distance. In the context of peer effects, these results highlight the importance of defining the reference group correctly. They suggest that interactions between neighbors occur at a very local level and that using an overly broad definition of neighborhood could dilute the effect of the relevant peers.

Overall, our findings suggest that interventions designed to improve college access among disadvantaged students—such as affirmative action—may have multiplier effects, something that should be incorporated into their evaluation.

Our findings add to two major strands of research. Firstly, they add to the literature studying the effects of affirmative action programs on the trajectories of underrepresented students in higher education. There is some controversy on whether affirmative action programs actually improve the outcomes of their intended beneficiaries. As discussed in Arcidiacono and Lovenheim (2016), there is some evidence that supports the so-called mismatch hypothesis: this is that less prepared applicants targeted by affirmative action would do better in less selective colleges (see for instance Arcidiacono et al. (2016)). Our results are more aligned with studies finding that affirmative action is beneficial for marginalized groups (Bleemer, 2021; Black et al., 2023; Bagde et al., 2016; Otero et al., 2021; Bleemer, 2022; Francis and Tannuri-Pianto, 2012; Mello, 2022; Bertrand et al., 2010). All previous studies focus on direct beneficiaries' enrollment outcomes, while a few of them look at graduation and labor market outcomes. To the best of our knowledge, we are the first to show that affirmative action programs also impact short- and medium-term effects on close peers of direct beneficiaries. By documenting a positive impact on siblings and neighbors, we highlight a more complex picture for how we should think about the benefits and costs of these policies.

Secondly, we contribute to recent work documenting large social spillovers on higher education trajectories. Our results are consistent with recent studies—see for instance Aguirre and Matta (2021); Altmejd et al. (2022); Barrios-Fernández (2022); Dahl et al. (2020)—showing that students' educational trajectories impact the choices of their peers. While these previous studies suggest that social spillovers could multiply the effects of programs that expand access to college for underrepresented groups, we are the first to show that this is indeed the case. We show that social spillovers expand the effects of a nationwide affirmative action program.

The rest of the paper is organized in five sections. Section 2 describes the educational institutions in Chile and the data we use in this project; Section 3 discusses our identification strategy; Section 4 presents results on the direct effects of BEA; Section 5 presents results on spillovers of BEA on the siblings and neighbors of its beneficiaries; Finally, Section 6 concludes. All supplemental material can be found in the Online Appendix.

2 Institutions and Data

This section starts by discussing some key features of the educational system in Chile. It then details the benefits and eligibility rules of the BEA. It concludes by describing the data and the samples we use in this project.

2.1 Education Institutions in Chile

In Chile, K-12 education is offered by public, voucher, and private schools. Public and voucher schools are subsidized by the state and cater for around 90% of the student population. In contrast, private schools are fully funded through tuition fees and cater for the other 10% of the student population.

There are three types of higher education institutions: vocational training centers, professional institutes, and universities (see Online Appendix A for further details). Only universities can grant bachelor's degrees and they concentrate 43% of the higher education enrollment.

Out of the 58 universities in the country, 18 are public and 40 are private. All public and nine private universities have selected their students through centralized admissions since the late 1960s. In 2012, other private universities began to join the centralized admission system. Currently, 45 universities select their students through it.

To apply to the universities participating in the centralized admission system, students have to take a national-level college admission exam and then apply to specific college-major combinations through an online platform.

Registering for the exam costs around USD 40. However, all students graduating from public and voucher high schools are eligible for a fee waiver. This results in roughly 90% of high school graduates registering for the exam. In the period that we study, the exam was applied in December—at the end of the academic year—and it had four sections: reading, mathematics, natural sciences, and social sciences.

The results of the exam are published a few weeks after its application. With their scores in hand, students submit an ordered rank of up to ten college-major combinations through an online platform. They are then allocated to the highest preference for which they are eligible by a deferred acceptance admission algorithm. Eligibility depends on students' academic performance, measured by a weighted average of their high school GPA and of their scores in the college admission exam.

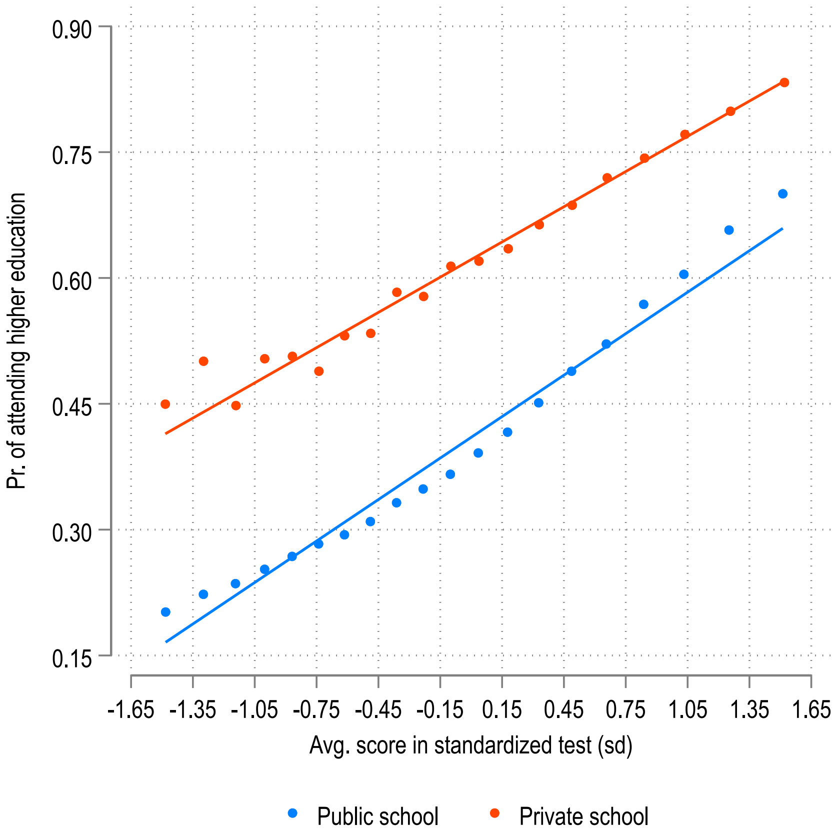
Since 2007 some of the places allocated through centralized admissions are reserved for disadvantaged students. The two main special admission programs integrated in the centralized system are the *"Beca de Excelencia Académica"* (BEA) and the *"Programa de Acceso a la Educación Superior"* (PACE). Section 2.2 describes the BEA in detail. Tincani et al. (2023) describes the PACE program in detail. The main difference between these two programs is that while the allocation of BEA places still depends on performance in the college admission exam, PACE places are allocated only based on high school GPA.

The rest of the universities have their own admission systems in place. Nevertheless, they still heavily rely on students' performance in the college admission exam.

Private and public universities charge similarly high tuition fees, and their students have access to similar financial aid opportunities. Most funding programs allocate resources depending on a combination of need and merit. Subsidized loans are available to students from households in the bottom 90% of the income distribution whose average score in the reading and mathematics sections of the admission exam is above 475. Roughly 60% of the students taking the college admission exam score above this threshold. Most scholarships focus on students from households in the bottom 60% of the income distribution and have higher academic requirements. Typically, students need an average score of 550 to be eligible for a scholarship. Roughly, 30% of the students taking the exam satisfy this criteria. Solis (2017) studies the Chilean setting and shows that eligibility for a student loan doubles college enrollment. Interestingly, eligibility for a scholarship does not make a difference for students who already qualify for a subsidized loan.

As described in the previous paragraph, the majority of the financial aid programs have a merit component. One exception is the "Free Higher Education" program, launched in 2015. This program fully covers the tuition fees of students from households in the bottom 60% of the income distribution who enroll in a university that participates in the program. Currently, there are 37 universities—18 public and 19 private—that are part of the program. Students attending other universities are still eligible for subsidized loans and scholarships.

Figure 1: Probability of enrolling in higher education by SES and Academic Performance



Notes: This figure illustrates the share of students enrolling in higher education depending on the type of high school that they attended—i.e., public or private—and on their performance in standardized tests. Students in public schools come from relatively disadvantaged settings and represent around one-third of the total high school enrollment. In contrast, private school students come from high SES households and represent less than 10% of the total high school enrollment. The horizontal axis plots students' average scores in the reading and mathematics section of a standardized exam applied at the end of grade 10. There is a large and persistent gap across social groups along the whole test score distribution.

Despite low application costs and the availability of generous funding, there are still large differences in university enrollment across social groups. Graduates from private high schools are considerably more likely to attend university than graduates from public and voucher schools. Part of this gap is explained by differences in their academic preparation, but the gap persists even after controlling for their academic potential. Figure 1 illustrates the gap in higher education enrollment between students in public and private high schools. There is a large and persistent gap along the whole academic performance distribution measured by students' average scores in standardized tests applied at the end of grade ten. There is a clear difference even among students obtaining very high scores.

2.2 *Beca de Excelencia Académica* (BEA)

BEA was introduced in 2007 with the objective of improving access to higher education among disadvantaged students with high academic potential. The main novelty of the program is that in addition to providing financial support, it created a new path to university for its beneficiaries.

As in the majority of the financial aid programs in Chile, eligibility for the BEA depends on both, need and merit. To be eligible for the BEA, students must come from households in the bottom 80% of the income distribution and attend a public or voucher high school. In addition, they need to graduate in the top 10% of their high school class.[3]

BEA beneficiaries receive around USD 1250 per year. This amount represents a 31% approximately of the average tuition charged by universities. This means that in general students eligible for BEA still need other sources of funding to pay for their studies. As BEA beneficiaries are particularly talented students—i.e., they come from the top 10% of their high school class—most of them qualify for other financial aid programs. Indeed, 80% of students graduating in the 10% of their high school class and taking the admission exam score above the student loans eligibility threshold. Thus, BEA does not make a huge difference for them in terms of funding.

BEA beneficiaries also receive an important advantage in terms of their admission probabilities. Universities participating in the centralized admission system reserve some places for BEA students. In 2022, the last year we analyze, these reserved seats represented a 4,1% of the 118.913 seats offered through centralized admissions. As regular seats, these reserved seats are also allocated by a combination of high school GPA and admission exam scores. Importantly, BEA students also compete for regular seats. Thus, these extra seats only increase their admission probability.

[3] Originally, students had to graduate in the top 5% of their high school class. In 2013 this requirement was relaxed to the top 7.5% and in 2014 to the top 10%.

2.3 Data

This paper uses administrative data from two public agencies: the Chilean Ministry of Education and the Department of Evaluation, Assessment, and Educational Records of the University of Chile (DEMRE). DEMRE is the agency in charge of the university admission system.

The Ministry of Education records that we use in this project cover the period 2002 to 2022. They include the universe of students enrolled in secondary and tertiary education and contain information on the schools students attend and their academic performance. The Ministry of Education also granted us access to a dataset identifying siblings attending school at the same time between 2002 and 2021.

DEMRE provided individual-level records of admissions exam scores and college applications for the years 2004 through 2022. We observe the scores of all students taking the exam, the rank of programs they submit when applying for college, their application score, and their admissions results. The data also contain demographic information. We observe self-reported socioeconomic characteristics, the national identification number of applicants' parents, and the address in which applicants lived in their senior year of high school.

Using these data we build a sample to estimate the direct effect of BEA on its beneficiaries and a sample to estimate the indirect effect of BEA on close peers of its beneficiaries. Below we describe both samples in detail:

2.3.1 Direct beneficiaries sample

The sample that we build to estimate the direct effects of BEA includes students reaching their senior year of high school between 2006 and 2021. Following the BEA eligibility criteria, we focus on students graduating from public and voucher schools. In addition, we restrict the sample to students whose high school GPA is near the top 10% of their class. We keep students whose GPA is within the optimal bandwidth for each sample, from the GPA defining the top 10%.[4] Following these criteria, we end with a sample of 185,988 students who were near the eligibility criteria for BEA.

In Chile, the grade scale goes from 1 to 7. Grades include one decimal point and the

[4]For the years in which BEA is available for students in the top 5% or in the top 7.5% we proceed in a similar way, but focusing on students near these thresholds.

high school GPA used to define eligibility for the BEA has two decimal points. Thus, in contrast to settings such as the US or the UK, the high school GPA in Chile is close to continuous.

Column (1) in Table 1 describes all students completing their secondary education in a public or voucher high school between 2006 and 2021 and graduating with a GPA within the optimal bandwidth that we computed to study changes in enrollment in higher education. Columns (2) and (3) present the same summary statistics, but for younger siblings and close neighbors of the students in column (1). Finally, column (4) presents summary statistics for the universe of students completing high school between 2006 and 2021.

The statistics presented in Table 1 do not vary much across columns. The largest differences arise when comparing students in column (1) with students in the rest of the columns. Indeed, women are over-represented among students whose high school GPA is near the BEA eligibility cutoff. This is consistent with recent evidence showing that female students perform better than male students in high school. Since the students near the BEA eligibility cutoff are among the best students in their cohorts, it is not surprising to find that on average they have higher GPAs and higher scores in the college admission exam than the rest of the students in the country. Their younger siblings also seem to perform slightly better in high school and in the college admission exam. This suggests that they come from households in which the children do better in school.

2.3.2 Indirect beneficiaries samples

To estimate the effects of BEA on the siblings and neighbors of its direct beneficiaries we expand the sample described in the previous section and create two independent samples in which we include direct beneficiaries younger siblings and neighbors.

To build the siblings sample we combine the data we have on family links provided by the Ministry of Education and by the DEMRE. Starting from the direct beneficiaries sample, we identify the oldest sibling that we observe for each family and we link him/her with him/her younger siblings. Thus, we end with a sample of 62.159 individuals connected to an average of 2,57 younger siblings. Column (2) in Table 1 describes all the younger siblings we linked to an individual from the direct beneficiaries sample within the optimal bandwidth.

Table 1: Summary Satistics

	Senior high school students within the OBW (1)	Students with an older sibling within the OBW (2)	Students with a close neighbor within the OBW (3)	All senior high school students (4)
Panel A: Demographic characteristics				
Female	61.28	49.52	52.99	51.95
Age when taking PSU	17.72	17.86	18.11	17.89
Panel B: Socioeconomic characteristics				
Low income (Q1)	52.05	40.42	59.96	54.01
Mid income (Q2-Q3)	37.59	44.01	34.86	37.74
High income (Q4-Q5)	10.36	15.57	5.17	8.24
Public high school	47.05	44.59	37.61	46.40
Voucher high school	52.95	52.19	57.79	53.60
Parental ed: primary education[b]	19.32	20.31	19.02	15.71
Parental ed: secondary education	48.63	49.51	52.44	49.19
Parental ed: higher education	20.13	37.93	38.18	17.54
Parental ed: 4-year college	12.76	17.29	10.18	10.64
Panel C: Academic characteristics				
High school GPA score	6.23	5.78	5.50	5.55
Avg. score in admission exam[a]	542.62	512.97	479.89	483.64
Observations	185,988	62,159	94,403	2,793,152

Notes: Column (1) presents summary statistics for students completing high school in the period 2006-2021 near the BEA eligibility cutoff (i.e., within the optimal bandwidth we compute to study the effects of BEA eligibility on enrollment in higher education). Columns (2) and (3) present summary statistics for the younger siblings and close neighbors of the students in column (1). Finally, column (4) presents summary statistics for the universe of students completing high school between 2006 and 2021.
[a] Average test score conditional on taking PSU
[b] Parental education refers to the maximum level of education reached by any of the applicant's parents.

We proceed in a similar way to build the neighbor sample. We follow Barrios-Fernández (2022) and link direct beneficiaries with neighbors who could apply to college one year after them. The geocoded data to which we have access allow us to identify neighbors in the three major urban areas of Chile: Santiago Metropolitan Region, Valparaíso Region, and Concepción Region. These three regions concentrate more than 60% of the country's student population. These data are available between 2004 and 2012. However, since the BEA started in 2007, for these analyses we focus on cohorts that could apply to college between 2007 and 2012. Column (3) in Table 1 describes our main neighbor sample. It includes the three closest neighbors of individuals in the direct beneficiaries sample who live within of 200 meters of them. This sample is restricted to younger neighbors who studied in public and voucher schools.

3 Identification strategy

3.1 Identification strategy

Identifying the effects of affirmative action programs on students' outcomes is challenging. Since these programs do not typically allocate their benefits at random, a naive comparison between beneficiaries and other students is likely to lead us to biased estimates of their causal effect.

This paper provides causal estimates of the effect of an affirmative action program—i.e., BEA—by exploiting quasi-random variation generated by its eligibility rules. As described in Section 2.2, eligibility for the BEA depends on students graduating in the top 10% of their high school class. Since in Chile, the high school GPA scale is close to continuous, this rule allows us to estimate the effect of BEA eligibility on students' outcomes using a regression discontinuity design. We will thus compare short- and long-term outcomes of students whose high school GPA situates them marginally below and marginally above the top 10% of their class.

Formally, let Y_{id} be the potential outcome of student i in the counterfactual case d, denoting whether the student is eligible for BEA ($d = 1$) or not ($d = 0$), and Y_i the observed outcome. Let z_i be the GPA normalized around student i's school-specific cutoff, so that $z_i \geq z^*$ implies that the student is eligible for BEA. We would like to compare eligible and non-eligible students in terms of their observed outcomes. Nonetheless, as discussed earlier, a naive comparison of these groups of students is likely to lead us to biased estimates, as we expect these students to differ in both observed and unobserved characteristics. We thus define our target parameter as $E[Y_{i1} - Y_{i0} \mid z_i = z^*]$, that is, the effects of BEA eligibility for students at the margin. In the case of Y_i being enrollment, we interpret our parameter as a first stage: those induced to attend college thanks to the BEA eligibility is also a measure of program's take-up. When we define Y_i as college graduation, then our target parameter is essentially an intent-to-treat (ITT) effect. We focus our analysis on ITTs in this last case as it is the right metric to assess the economic incidence of the BEA policy.

We posit the following linear regression to identify the effects of BEA on those arbitrarily close to the eligibility cutoff (Hahn et al., 2001):

$$Y_i = \alpha + \beta \mathbf{1}\{z_i \geq z^*\} + k(z_i) + u_i, \tag{1}$$

where $k(z_i)$ is a polynomial function whose parameters are allowed to differ to the left and right of the school-specific cutoff. The term β identifies $E[Y_{i1} - Y_{i0} \mid z_i = z^*]$ under the continuity assumption of $E[Y_{id} \mid z_i]$ at the cutoff $z_i = z^*$. We follow the standard practices of examining the presence of bunching in the density of z_i and of discontinuities in baseline covariates to assess the plausibility of such assumption (see next Section). Finally, in the estimation of the above equation, we include cohort-specific fixed effects and cluster standard errors at the school-cohort level.

We proceed in a similar way to estimate the effects of BEA on the close peers of its beneficiaries. We rely once more on specification 1, but instead of focusing on BEA beneficiaries' outcomes, we look at the outcomes of their younger siblings and neighbors. We thus compare the outcomes of individuals who have slightly older peer marginally receiving or losing the BEA. As discussed in Altmejd et al. (2022) and Barrios-Fernández (2022), this approach overcomes the main identification challenges that arise in the context of peer effects, namely the existence of correlated effects and the reflection problem.[5]

Following the identification result from Hahn et al. (2001), we restrict the sample to those in the proximity of z^*. We follow Calonico et al. (2020) to choose our optimal bandwidths. For our results, we optimally set different bandwidths for different outcomes, as they are associated with different sample sizes. Nevertheless, Online Appendix B.1 shows that the optimal bandwidths in each case are fairly close to each other, setting a very narrow window around the eligibility cutoff, which is possible thanks to our large sample sizes. Furthermore, in the Online Appendix, we show that our results are robust to different bandwidth choices.

3.2 Validity

The validity of our regression discontinuity design relies on our continuity assumption stated in the previous section. To assess the plausibility of such assumption and to assess the extent of potential manipulation which would violate such condition, we conduct two

[5]See Manski (1993), Manski (1995), and Angrist (2014) for a detailed discussion of the identification challenges of peer effect.

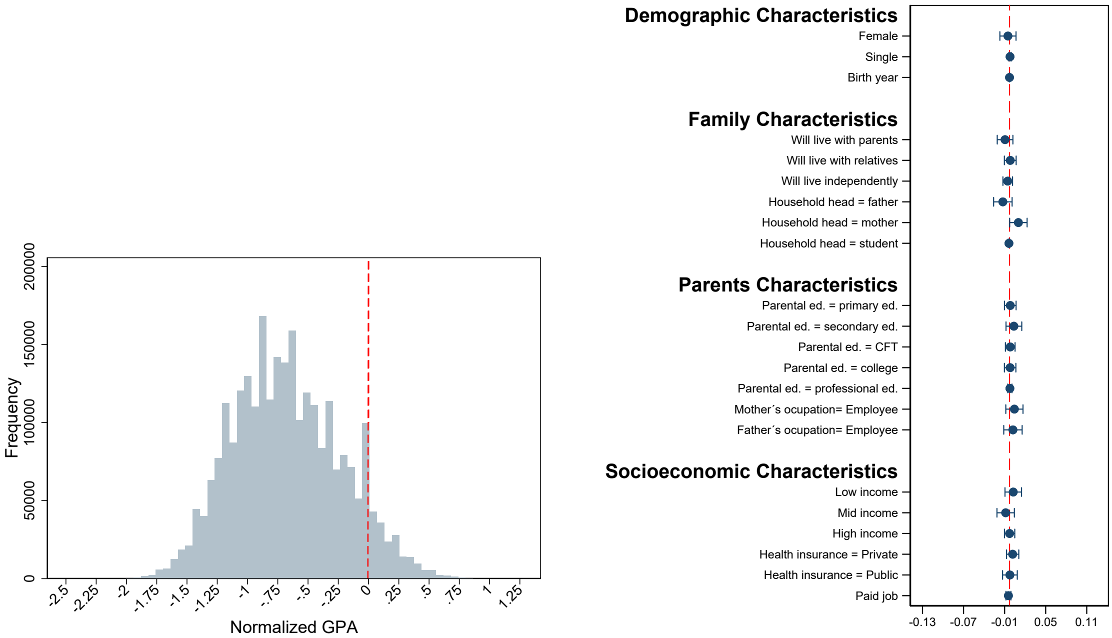
exercises: (i) we study the density of the running variable around the cutoff, and (ii) we test for discontinuities in potential confounders at the eligibility threshold.

We provide supportive evidence of the continuity assumption in Figure 2. In Panel (a) of this figure, we plot the distribution of the high school GPA centered around the school-specific cutoff that defines eligibility for BEA. The distribution looks smooth around the cutoff, except from an excess of mass—i.e., bunching—that arises exactly at zero. This is, however, a mechanical result. In each high school class, there is a finite number of grades (for example, the average size of a high school class in Chile is 102). Normalizing the high school GPA around the BEA eligibility cutoff guarantees a normalized GPA exactly at zero, but not at other points of the distribution. To confirm that this bunching is just a mechanical result, Online Appendix B.2 shows that a similar spike arises when normalizing high school GPA around the BEA eligibility cutoff for cohorts that completed high school before its introduction; and also when normalizing the high school GPA around arbitrarily chosen points that do not determine eligibility for BEA or other benefits. Therefore, we proceed by eliminating observations with GPA right at the eligibility cutoff (at zero for our normalized running variable). Online Appendix B.3 checks that our main results hold even if we include these observations.

Panel (b) of Figure 2 studies discontinuities in potential confounders at the cutoff. For this figure, we estimate specification (1) using as outcomes a rich vector of predetermined students' characteristics. As the figure documents, we find precisely estimated effects around zero for all the potential confounders we study.

Finally, as discussed in Section 2, BEA eligibility depends on students' high school graduation rank. Thus, to manipulate their eligibility for BEA, students would need to be able to have modify their high school GPA. This variable takes into account a student's performance in each subject between grades 9 and 12. In high school, most subjects are taught by different teachers. This and the difficulty to anticipate the grade associated to a specific percentile of the high school GPA distribution makes manipulation unlikely. Students might exert some effort to improve their grades, but these efforts are likely to be smooth around the cutoff. Overall, we find no evidence suggesting that our RDD estimates are invalid due to potential manipulation.

Figure 2: Validity of identification strategy



(a) Distribution of running variable

(b) RD estimates on selected covariates

Notes: The figure presents evidence supporting our identification strategy. Panel (a) shows an histogram of our running variable. The running variable corresponds to the distance of the student's GPA to her school-level BEA cutoff. Panel (b) presents RD estimates on selected covariates. We estimate equation (1) taking as dependent variables the following baseline individual-level characteristics: The figure depicts 95% confidence intervals based on standard errors clustered at the school level.

4 Direct effects of BEA

Having shown evidence supporting our identification assumptions, we now turn to document BEA-eligibility effects on its direct potential beneficiaries. We study enrollment and graduation effects for high school graduates near the margin of eligibility. We also study potential mechanisms, backing the idea that the documented effects are driven by the reserved-seat policy.

4.1 Effects on educational trajectories

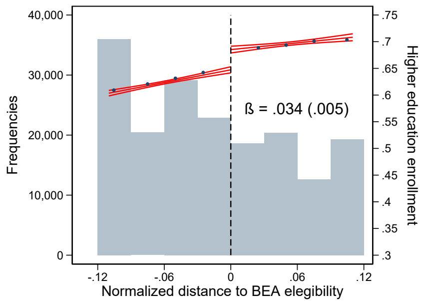
Figure 3 visually compares educational trajectories of barely eligible and non-eligible students. The figure shows fitted linear specifications, comparing each outcome with our running variable (normalized GPA). For clarity in the following figures, we estimate the fitted lines using the optimal bandwidth shown in appendix B.1. Panels (a) and (b) shows effects for higher education enrollment and four-year institutions. The difference between these two estimates is that, in the latter case, we exclude vocational institutions which grant two- and four-year degrees. The RD plots show a clear jump in the likelihood of enrollment in higher education (panel a), nevertheless, this effect is mostly driven by an increase in enrollment in four-year institutions. As BEA provides reserved seats only for four-year institutions, we see our estimated effects as consistent with the reserved seat policy as the main driver of the effects we show. We come back to this point later in Section 4.2.

Table 2 presents the formal RDD estimates from equation (1). The table, in panel (a), shows the estimated effects of BEA eligibility on the probability of enrollment in higher education and on four-year degrees majors. Being eligible for BEA increases the likelihood of enrollment in a higher education institution by 3.4 percentage points. We confirm what we visually anticipated, regarding the larger effect on four-year degree enrollment: BEA eligibility increases the probability of attending a four-year degree by 4.3 percentage points. Given the counterfactual mean of 49%, the estimated effect represents a 9% increase. The effect is larger for female (5.3 percentage points) than for male students (2.7 percentage points).

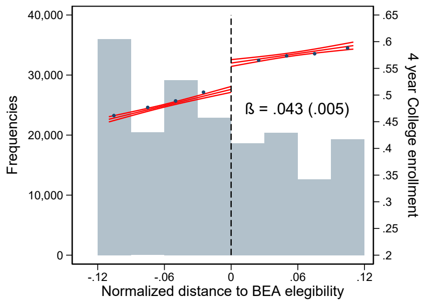
While BEA increases the likelihood of attending higher education, a policy-relevant question is whether it drives eligible students to high- or low-quality institutions—that is, with potential high value-added —and/or more or less selective ones. We first approach this question in Panels (c) and (d) of Figure 3. For Panel (c), we compute the average score in college admission test for each college-major combination and identify the top 25% majors in the system for each year. The figure suggests a positive effect of BEA eligibility on the likelihood of enrolling in a high-quality institution. Likewise, Panel (d) shows a similar effect on the probability of enrolling in a top 25% institution according to expected earnings. The estimates in Panel B of Table 2 confirm the previous visual inspection. Barely eligible students are 2.3 percentage points more likely to enroll in a top 25% school, a 12% increase with respect to the counterfactual mean. The effect is similar (2.1 percentage points) if we consider enrolling in a top 25% institution in the distribution of expected earnings. We again estimate larger effects for females.

Since BEA is causing an inflow of low-performing students to high-quality and selective majors, a point to consider in the equity-efficiency trade-off debate of affirmative action policies is whether beneficiaries are sufficiently proficient. Panels (e) to (h) of Figure 3 study this by looking at differences in graduation from different types of higher education

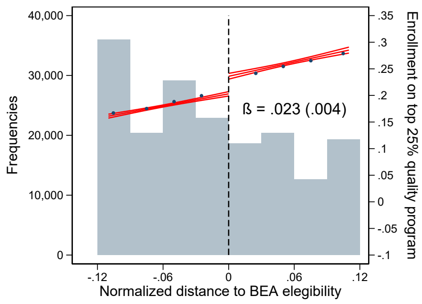
Figure 3: Effects of BEA Eligibility on Higher Education Trajectories



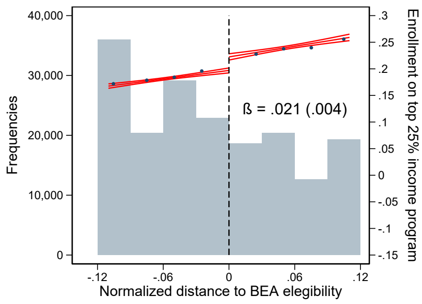
(a) Higher Ed. enrollment



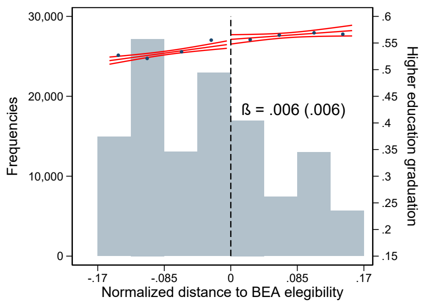
(b) Four-year college enrollment



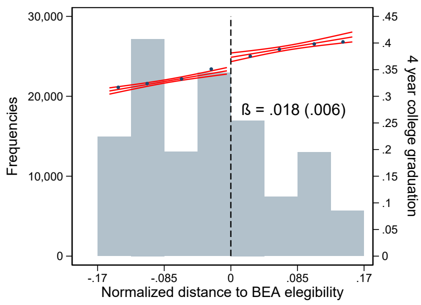
(c) Top 25% enrollment (selectivity)



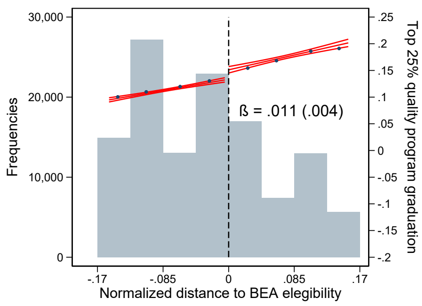
(d) Top 25% enrollment (expected earnings)



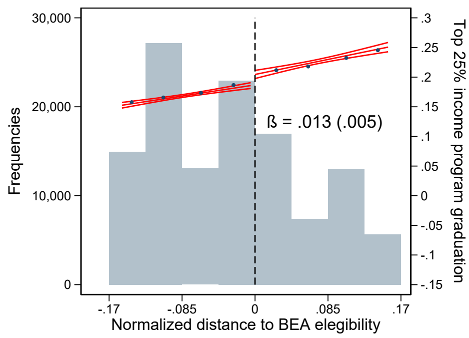
(e) Higher Ed. Graduation



(f) Four-year college graduation



(g) Top 25% graduation (selectivity)



(h) Top 25% graduation (expected earnings)

Notes: The figure shows regression discontinuity plots across a set of short- and long-term outcomes. The running variable—i.e., high school GPA—is centered around the GPA defining eligibility for the BEA for each cohort and each high school. Blue dots correspond to outcome means at different values of the running variable. The red lines represent linear fits of the outcome on the running variable on each side of the BEA eligibility threshold. The background blue bars illustrate the running variable's distribution around the cutoff. The range used for these plots corresponds to optimal bandwidths for four-year college enrollment (panels a to d) and for higher education graduation (panels e to f) computed according to Calonico et al. (2020). Panel (a) studies the probability of attending higher education; panel (b) the probability of attending a four-year college; panel (c) the probability of enrolling in a degree in the top 25% of the selectivity distribution; and panel (d) the probability of enrolling in a degree with high expected earnings. The selectivity of a degree corresponds to the average score of its admitted students in the college admission exam. Expected earnings correspond to the average earnings of former students four years after graduation. Panels (e) to (h) replicate the previous analyses, but looking at graduation.

Table 2: Effect of BEA eligibility on college enrollment and graduation

	All (1)	**Female (2)**	**Male (3)**	**All (4)**	**Female (5)**	**Male (6)**
	Panel A - Enrollment on Higher Education					
	Any HEI			4-year college		
Eligible for BEA	0.034***	0.044***	0.021***	0.043***	0.053***	0.027***
	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)
Observations	185988	113977	72011	185988	113977	72011
Counterfactual Mean	0.632	0.612	0.663	0.490	0.479	0.506
	Panel B - Quality of the higher ed. degree					
	Degree in the top 25% of selectivity)			Degree in the top 25% of expected earnings		
Eligible for BEA	0.023***	0.028***	0.018***	0.021***	0.022***	0.020***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.007)
Observations	185988	113977	72011	185988	113977	72011
Counterfactual Mean	0.188	0.162	0.229	0.192	0.160	0.241
	Panel C - Graduation from higher education					
	Any HE			4-year college		
Eligible for BEA	0.006	0.012	-0.005	0.018***	0.023***	0.008
	(0.006)	(0.008)	(0.010)	(0.006)	(0.007)	(0.009)
Observations	131340	78765	52575	131340	78765	52575
Counterfactual Mean	0.519	0.568	0.447	0.326	0.362	0.272
	Panel D - Quality of higher education degree (graduation)					
	Graduation from degree in the top 25% of selectivity)			Graduation from degree in the top 25%of expected earnings		
Eligible for BEA	0.011***	0.013**	0.006	0.013***	0.015**	0.009
	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)	(0.008)
Observations	131340	78765	52575	131340	78765	52575
Counterfactual Mean	0.116	0.111	0.123	0.169	0.160	0.183

Notes: The table shows RDD-based estimates for a set of short- and long-term outcomes. The running variable—i.e., high school GPA—is centered around the GPA defining eligibility for the BEA for each cohort and each high school. The samples used in the table variate by gender. Columns (1) and (4) were estimated using all direct beneficiaries; columns (2) and (5) are restrained to females and columns (3) and (6) are restrained to males. The optimal bandwidths used for enrollment (panels a and b) and for graduation (panels c to d) outcomes were computed according to Calonico et al. (2020) using as outcomes four-year college enrollment and graduation respectively. Columns (1), (2), and (3) of panel (a) study the probability of attending higher education, the other three columns show the probability of attending a four-year college. In panel (b) columns (1), (2) and (3) study the probability of enrolling in a degree in the top 25% of the selectivity distribution; and columns (4), (5), and (6) study the probability of enrolling in a degree with high expected earnings. The selectivity of a degree corresponds to the average score of its admitted students in the college admission exam. Expected earnings correspond to the average earnings of former students four years after graduation. Panels (c) to (d) replicate the previous analyses, but looking at graduation. We control for cohort and school fixed effects. We cluster standard errors (in parenthesis) at the school×cohort level. *,**,*** indicate statistical significance at the 10, 5, and 1% levels.

institutions. We find no statistically significant effect on the probability of graduating from higher education. This, however, does not mean that the program is ineffective as the affirmative action component of BEA aims only at four-year majors. Consistently, the RD plots suggest positive impacts on graduating from four-year colleges and relatively more selective colleges. Table 2, panels (b) and (c), shows that BEA eligibility increases the probability of graduating from a four-year college by 1.1 percentage points, a 6% increase with respect to the counterfactual mean. Furthermore, BEA increases the likelihood of graduating from a top 25% quality major by 1.1 percentage points (9.5% increase). We find a similar effect for the probability of a top 25% graduation in the ranking of students' expected earnings by major.

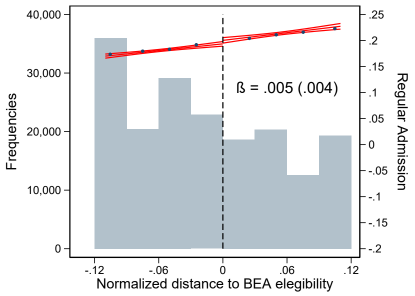
4.2 Drivers of BEA Effects

This section investigates the drivers of the BEA effects that we find on students' higher education trajectories. As discussed in Section 2.1, in addition to reserving some seats for its beneficiaries, BEA also offers them some financial support. To assess the relevance of these two components of BEA we conduct a series of analyses, which results we present in Figure 4.

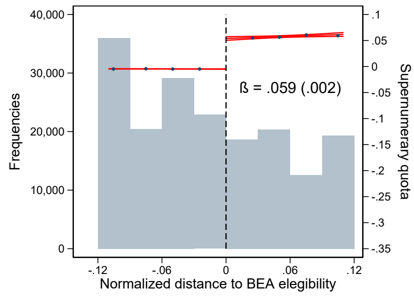
Firstly, we study changes in the admission path of BEA beneficiaries. Panel (a) shows that there is no significant change in their probability of being admitted through the regular admission path. In contrast, panel (b) indicates that there is a large and significant effect on their probability of being admitted in one of the reserved seats. The magnitude of this increase is slightly larger than the increase we find in 4-year college enrollment. This is likely a result of non-BEA beneficiaries compensating part of the difference we find on admissions by enrolling in 4-year colleges that do not take part in the centralized admission system. In any case, these results suggest that an important part of the effect that we find on college enrollment is driven by the reserved seats that BEA makes available for talented students from disadvantaged backgrounds.

We then study whether BEA-eligible students become more likely to take the college admission exam and to qualify for funding. Panels (c) and (d) suggest that this is not the case. Having a high-school GPA above the BEA eligibility cutoff does not significantly increase the probability of taking the college admission exam or of obtaining a score above 475, which is the score required to be eligible for subsidized student loans. Thus, credit

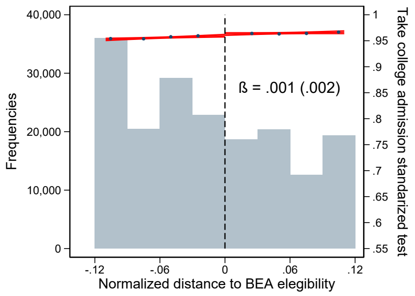
Figure 4: Drivers of BEA Eligibility Effects on Higher Education Trajectories



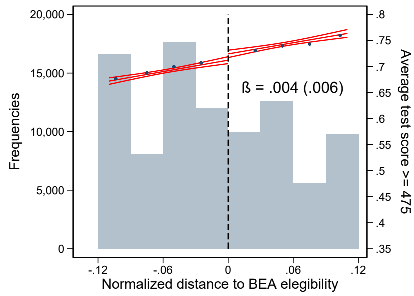
(a) Regular admissions



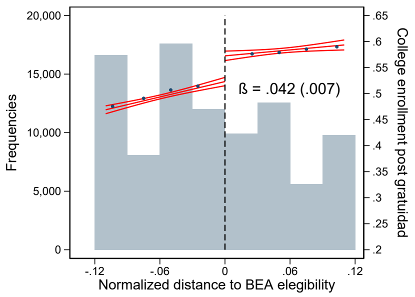
(b) Special admissions



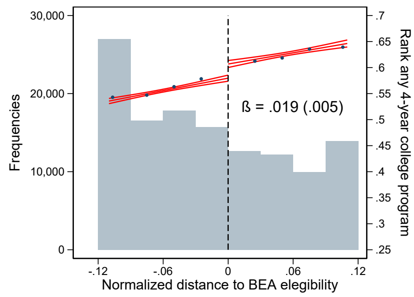
(c) Taking the college admission exam



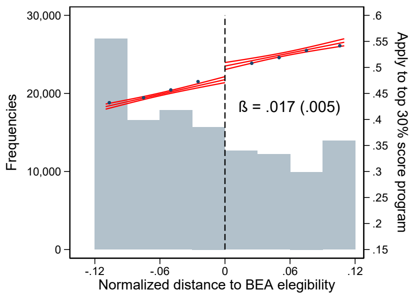
(d) Scoring above funding cutoff



(e) Enrollment after "Free Higher Ed."



(f) Applying to 4-year colleges in CAS



(g) Applying to highly selective program

Notes: The figure shows regression discontinuity plots for outcomes characterizing the high school-to-college transition. The running variable—i.e., high school GPA—is centered around the GPA that defines eligibility for BEA in each cohort and high school. Blue dots correspond to outcome means at different values of the running variable. The red lines represent linear fits of the outcome on the running variable independently estimated on each side of the BEA eligibility threshold. The blue bars illustrate the running variable's distribution around the cutoff. The range used for these plots corresponds to optimal bandwidths for four-year college enrollment computed according to Calonico et al. (2020). Panels (a) and (b) study the probability of being admitted to 4-year colleges that participate of centralized admissions through regular and special BEA quotas; panel (c) the probability of taking the college admission exam and panel (d) the probability of scoring above 475 points—i.e., the score required to be eligible for a subsidized student loan. Panel (e) panel the probability of enrolling in college in the period 2016-2022, during which students in the bottom 60% of the income distribution were eligible for "Free Higher Education". Finally, panels (f) and (g) study the probabilities of applying to any degree through the centralized admission system, and to a program among the 25% most selective in the country, respectively. The selectivity of a degree corresponds to the average score of its admitted students in the college admission exam.

constraints on both sides of the BEA eligibility threshold are similar, suggesting once more than the reserved seats of BEA are the main driver of the effects we find on enrollment and graduation.

In line with these results, in panel (e) we show that the effect on college enrollment for cohorts graduating from high school after the implementation of "Free Higher Education" is very similar to the effect that we document in Section 4.1. The "Free Higher Education" program was implemented in 2015 and it offers all students from households in the bottom 60% of the income distribution to attend higher education for free. In contrast to student-loans and scholarships, this program does not have academic any requirements. All students admitted to a higher education institution participating in the program receive a tuition fee waiver. Finding that the BEA-eligibility effect on college enrollment remains almost unchanged after a significant increase in the generosity of the funding available for disadvantaged students also suggests that reserved seats are the key driver of the BEA effects.

As shown in panels (f) and (g) being eligible for BEA makes students more likely to apply to a 4-year college participating in the centralized admission system and to a college program among the top 25% most selective programs in the country. The admission advantages that BEA offers them seem to encourage eligible students to apply to be more ambitious and apply to more selective colleges.

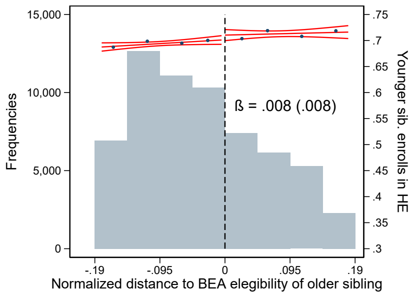
5 Spillover effects of BEA

The evidence presented in Section 4 indicates that eligibility for BEA improves the postsecondary educational trajectories of its direct beneficiaries. In this Section, we show that it also improves the postsecondary educational trajectories of their younger siblings and close neighbors. These close peers of BEA direct beneficiaries also become more likely to enroll and to graduate from a four-year college.

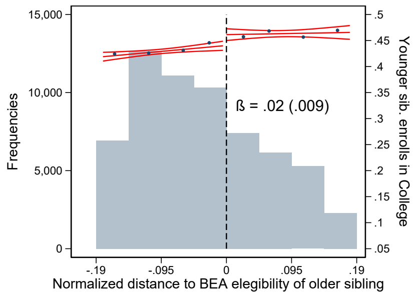
5.1 Sibling spillovers

This Section investigates changes in the postsecondary educational trajectories of the younger siblings of direct beneficiaries. For these analyses, we focus on younger siblings who are old enough to attend college in the period that we study (i.e., who became 18

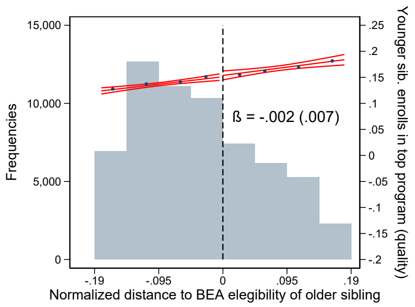
Figure 5: Effect of BEA Eligibility on Younger Siblings' Educational Trajectories



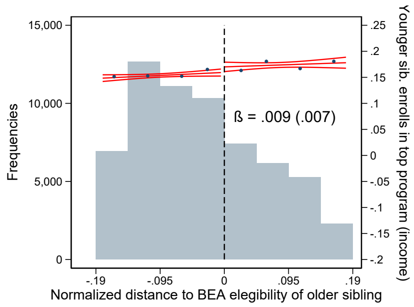
(a) Higher Ed. enrollment



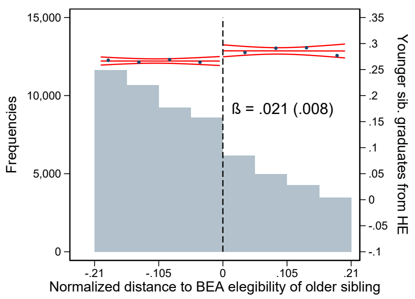
(b) Four-year college enrollment



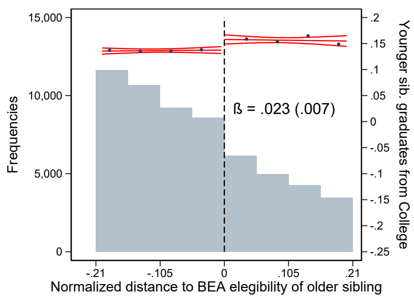
(c) Top 25% enrollment (selectivity)



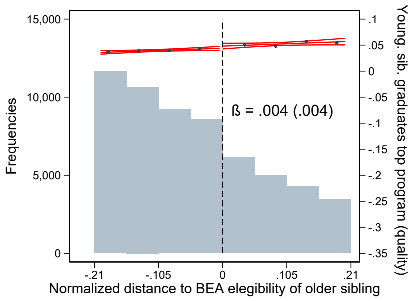
(d) Top 25% enrollment (expected earnings)



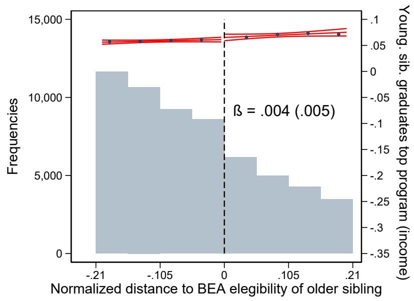
(e) Higher Ed. Graduation



(f) Four-year college graduation



(g) Top 25% graduation (selectivity)



(h) Top 25% graduation (expected earnings)

Notes: The figure shows regression discontinuity plots across a set of short- and long-term outcomes of younger siblings of direct beneficiaries. The figure shows regression discontinuity plots across a set of short- and long-term outcomes. The running variable—i.e., high school GPA of older sibling—is centered around the GPA defining eligibility for the BEA for each cohort and each high school. Blue dots correspond to outcome means at different values of the running variable. The red lines represent linear fits of the outcome on the running variable on each side of the BEA eligibility threshold. The background blue bars illustrate the running variable's distribution around the cutoff. The range used for these plots corresponds to optimal bandwidths for four-year college enrollment (panels a to d) and for higher education graduation (panels e to f) computed according to Calonico et al. (2020). Panel (a) studies the probability of attending higher education; panel (b) the probability of attending a four-year college; panel (c) the probability of enrolling in a degree in the top 25% of the selectivity distribution; and panel (d) the probability of enrolling in a degree with high expected earnings. The selectivity of a degree corresponds to the average score of its admitted students in the college admission exam. Expected earnings correspond to the average earnings of former students four years after graduation. Panels (e) to (h) replicate the previous analyses, but looking at graduation.

Table 3: Effect of peer elegible for BEA

	Siblings ***(1)***	***Neighbors*** ***(2)***
	Panel A - Enrollment	
Higher education	0.008	-0.004
	(0.008)	(0.006)
4-year college	0.020**	0.023***
	(0.009)	(0.008)
Top 25% program (selectivity)	-0.002	0.006
	(0.007)	(0.004)
Top 25% program (expected earnings)	0.009	0.005
	(0.007)	(0.005)
	Panel B - Graduation	
Higher education	0.021**	0.009
	(0.008)	(0.007)
4-year college	0.023***	0.019***
	(0.007)	(0.006)
Top 25% program (selectivity)	0.004	0.001
	(0.004)	(0.003)
Top 25% program (expected earnings)	0.004	0.007
	(0.005)	(0.004)

Notes: This table shows RDD-based estimates of BEA eligibility on college choices and outcomes of close peers. The estimates are based in estimation of equation (1). The running variable—i.e., high school GPA—is centered around the GPA of the older peer, defining eligibility for the BEA for each cohort and each high school. The optimal bandwidths used for enrollment (Panel a) and for graduation (Panel b) outcomes were computed according to Calonico et al. (2020) using as outcomes four-year college enrollment and graduation respectively. The dependent variable corresponds to college enrollment (Panel a) and college graduation (Panel a) of close peers. Column (1) shows estimates for younger siblings and column (2) for close neighbors. We control for cohort and school fixed effects. We cluster standard errors (in parenthesis) at the school×cohort level. *,**,*** indicate statistical significance at the 10, 5, and 1% levels.

years old between 2007 and 2022).

Figure 5 and Table 3 summarize the results of this section. Panels (a) and (b) of Figure 5 show that although having an older sibling marginally eligible for BEA does not increase enrollment in higher education in general, it does increase enrollment in four-year colleges. Indeed, the younger siblings of students marginally eligible for BEA are 2 percentage points (4.5%) more likely to attend a four-year college than the younger siblings of students who barely fail to qualify for BEA. This spillover effect is large, as it represents 46.5% of the effect we find for students who become eligible for BEA themselves. In contrast to what we find for direct beneficiaries of BEA, their younger siblings do not seem to become more likely to attend a more selective program (panel c) or a program associated with high earnings (panel d).

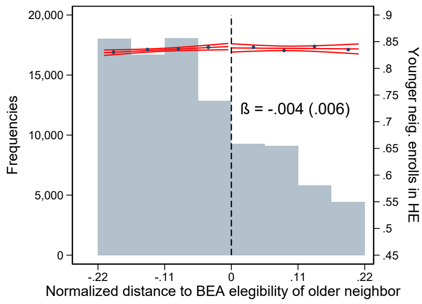
As in the case of direct beneficiaries, we also study whether the differences that we find in enrollment translate into differences in graduation. As shown in panels (e) and (f) of Figure 5 they do. The younger siblings of students marginally eligible for BEA are 2.1 percentage points (8%) more likely to graduate from higher education and 2.3 percentage points (20%) more likely to graduate from a four-year college. These results suggest that the younger siblings induced to attend a four-year college by their older siblings actually benefited from it, as they were able to complete their studies.

Finally, and consistently with the null effects on enrollment at very selective programs or at programs associated with high earnings, we do not find evidence of an increase in graduation from these types of programs. The point estimates we find are small and precisely estimated.

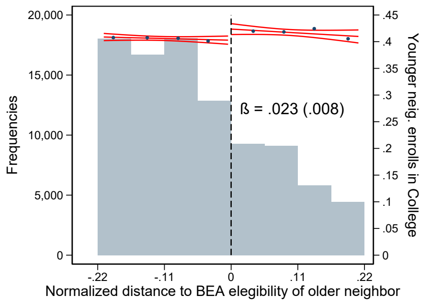
5.2 Neighbor spillovers

We follow the same structure as previous section in showing spillover effects on neighbors. In this case, we study post-secondary choices and outcomes for neighbors residing less than 200 meters away from the direct beneficiaries' home. Within this range, we choose up to three neighbors (the closest ones). We also restrict the sample to close neighbors graduating from public or private-voucher schools only one year after the direct beneficiary graduate from high school. Figure 6 shows the RD plots illustrating effects of neighbors' BEA eligibility on enrollment and graduation. Panels (a) and (b) show effects on enrollment in any institution and in a four-year college. As with the case with siblings, we do not find effects on enrollment in any type of post-secondary institution (panel a). However, panel (b) does evidence an increase in the probability of five-year enrollment. Table 3 confirms these assertions. Neighbor's BEA access increases the likelihood of attending

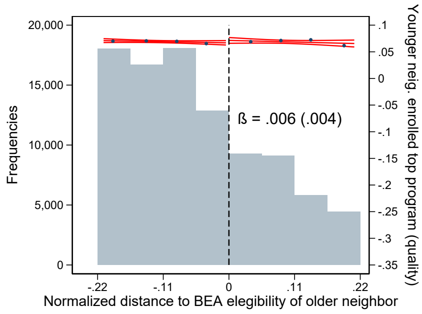
Figure 6: Effect of BEA Eligibility on Close Neighbors' Educational Trajectories



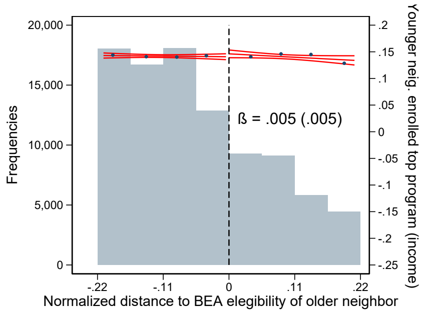
(a) Higher Ed. enrollment



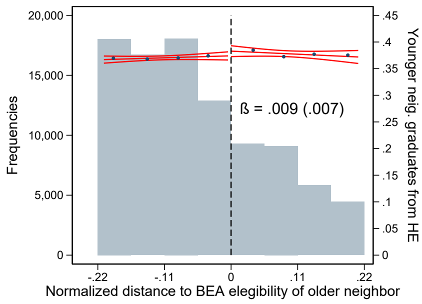
(b) Four-year enrollment



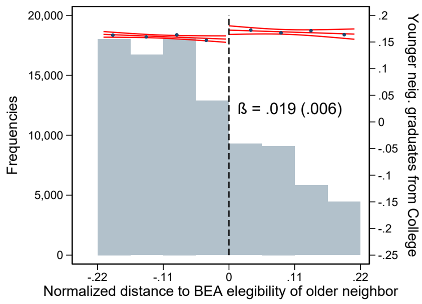
(c) Top 25% enrollment (selectivity)



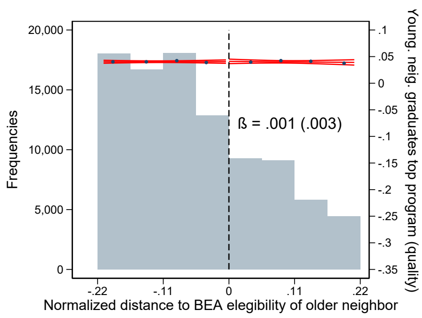
(d) Top 25% enrollment (expected earnings)



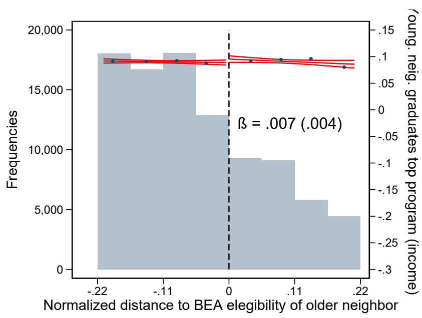
(e) Higher Ed. Graduation



(f) Four-year college graduation



(g) Top 25% graduation (selectivity)



(h) Top 25% graduation (expected earnings)

Notes: The Figure shows regression discontinuity plots across a set of short- and long-term outcomes of close neighbors of direct beneficiaries. The sample consists of the three closest neighbors within a 200-meter radius who graduate from public or voucher high schools one year after the oldest neighbor. The figure shows regression discontinuity plots across a set of short- and long-term outcomes. The running variable—i.e., high school GPA of older neighbor—is centered around the GPA defining eligibility for the BEA for each cohort and each high school. Blue dots correspond to outcome means at different values of the running variable. The red lines represent linear fits of the outcome on the running variable on each side of the BEA eligibility threshold. The background blue bars illustrate the running variable's distribution around the cutoff. The range used for these plots corresponds to optimal bandwidths for four-year college enrollment (panels a to d) and for higher education graduation (panels e to f) computed according to Calonico et al. (2020). Panel (a) studies the probability of attending higher education; panel (b) the probability of attending a four-year college; panel (c) the probability of enrolling in a degree in the top 25% of the selectivity distribution; and panel (d) the probability of enrolling in a degree with high expected earnings. The selectivity of a degree corresponds to the average score of its admitted students in the college admission exam. Expected earnings correspond to the average earnings of former students four years after graduation. Panels (e) to (h) replicate the previous analyses, but looking at graduation.

a five-year college by 2.3 percentage points (a 6% increase).

Panels (c) and (d) of Figure 6 investigate effects on the quality margin in enrollment decisions. In this case, we do not see clear jumps in the probability of enrollment in selective institutions at the eligibility cutoff. Moreover, the estimates from Table 3 confirm that the effects are not statistically significant.

Graduation effects for close neighbors show patterns that again are not consistent with the mismatch hypothesis. Panels (e) and (h) assess graduation impacts on the neighbors of marginally eligible students. Consistent with the previous evidence, we do not find effects on graduating from any institution. Panel (f), however, indicates a potential positive impact on graduating from a four-year degree. Table 3 indicates that BEA eligibility increases neighbors' probability of graduating from a five-year college by 1.9 percentage points, corresponding to a 13% increase with respect to the baseline. We find no effects on graduation for selective institutions, consistent with enrollment effects.

Overall, we find that the effects on neighbors and siblings are largely consistent. We find that eligibility to BEA affects both neighbors' and siblings' likelihood of attending and graduating from four-year colleges. Furthermore, the effects on close neighbors and siblings are strikingly similar in terms of magnitude. The robustness of our estimates across types of peers brings support to the hypothesis that peers are indeed being affected.

5.3 Drivers of Social Spillovers

So far, we have documented significant spillover effects in college outcomes from BEA eligibility, both for siblings and close neighbors. We now discuss what drives these changes in outcomes.

The documented changes in enrollment and graduation can be driven by pure changes in behavior conditional on a stock of human capital, or by changes in peers' human capital. Either by information clearance or by a change in preferences, close peers might change their choices in terms of college-related application and enrollment, without necessarily providing more effort in acquiring more skills that would lead them to have higher chances of getting into college. Alternatively, the older peer's access to BEA might affect human capital investment for forward-looking students (again, thanks to having more information or by a change in preferences). This effect can be a response of a higher effort in acquiring more skills to have a higher PSU score and/or try to reach the BEA cutoff. In this section, we show evidence consistent that the human capital channel does not seem to play a role in explaining our main effects.

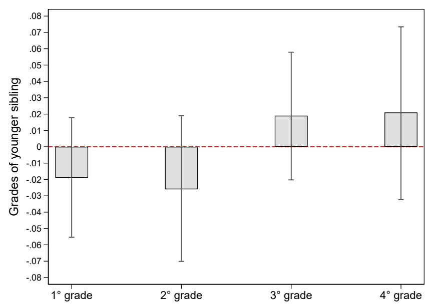
Figure 7 presents peer eligibility effects on younger siblings' performance in high school and PSU enrollment. Panel (a) presents GPA effects across the younger sibling's high school years. For this figure, the sample for each estimate (depicted in bars) is different; we define our sample to we make sure that each potential beneficiary of BEA had a sibling young enough to have been at school (in each grade level) while the older sibling was graduating from high school. Across all high school years, we do not find statistically significant effects.

Panels (b) and (c) of Figure 7 explore effects on PSU take-up and performance for younger siblings. Panel (b) shows effects on PSU enrollment and Panel (c) effects on PSU scores conditional on take-up. We estimate a small effect of 0.1 percentage points, which is not statistically significant. Given the lack of change in composition, we can interpret our RD estimates on PSU conditional on take-up as close to the causal effects on PSU score. Panel (c) shows a estimated effect of 2.9 PSU points, approximately 0.06 standard deviations, which is not statistically significant. The corresponding standard error equals 1.9 PSU scores, or 0.04 standard deviations, implying that we cannot rule out small effects.

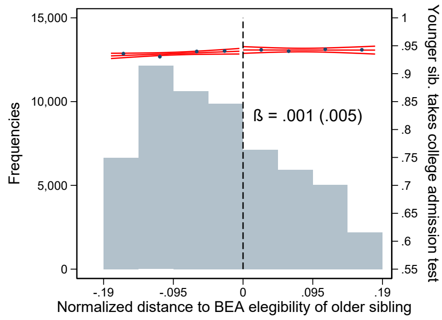
Panels (d) and (e) show effects on application behavior to college. If students are not induced to invest more in their human capital by their siblings' access to BEA, then the effects on enrollment should be explained by changes in college choices. Panel (d) presents the RD plot relating funding application and our running variable. The figure shows no effects on funding applications. Panel (e) depicts the effect of siblings' access to BEA on individuals' application to college. While noisy, there is some evidence that the younger siblings of students eligible for BEA are more likely to apply to one of the colleges that participate of the centralized admission system.

Figure 8 presents the same set of estimates from Figure 7 but applied to close neighbors instead. Specifically, we explore whether students are induced to invest in their human capital when a close neighbor has access to BEA. In line with evidence from siblings, we do not find effects on high school GPA (Panel a), PSU enrollment (Panel b), or PSU scores conditional on enrollment (Panel c). Panels (d) and (e) show effects on funding and college likelihood. As with the case of siblings, there are no effects on funding applications and a not precisely estimated, but positive impact on college applications. Overall, our results

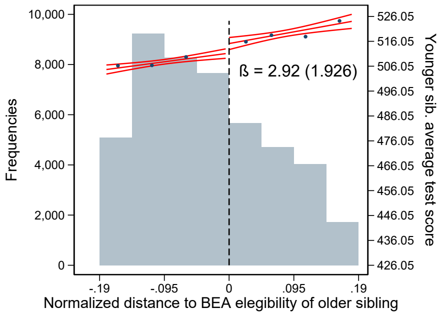
Figure 7: Effects of older sibling's BEA eligibility on the younger siblings' educational performance and PSU take-up



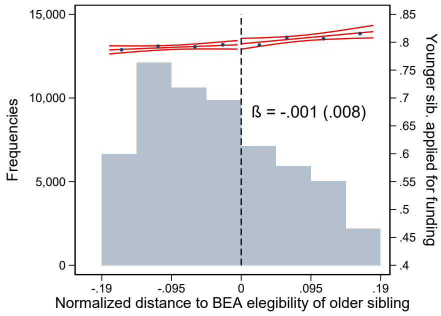
(a) High school GPA



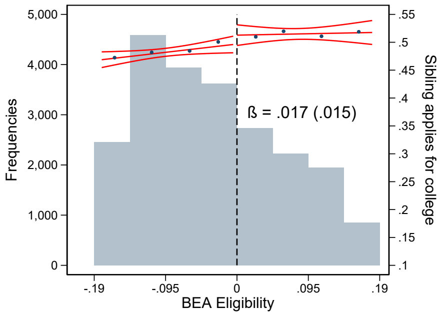
(b) Pr. of taking the admission exam



(c) Test scores (conditional on take-up)



(d) Pr. of apply for funding



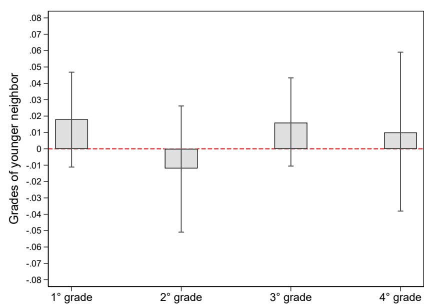
(e) Pr. of apply to college

Notes: The Figure shows RDD estimates of older-sibling BEA eligibility status on younger's siblings educational performance. Panel (a) presents effects on GPA across high school years. Panel (b) shows BEA effects on taking college admission test. Panel (c) presents effects on college admission test score, conditional on take-up and panel (e) show the probability of aplly to college. in Panels (b) and (c), we show the OLS estimate of equation (1) and its standard error in parenthesis (clustered at the school level).

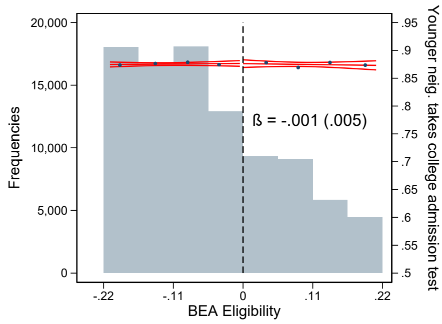
reject the hypothesis that the close peers of direct beneficiaries that we study—i.e., younger siblings and close neighbors— increase their investments in human capital during high school. We do not find evidence of them improving their high school GPA and there is only a small improvement on their scores in the college admission exam (i.e., less than 3% of a standard deviation). Therefore, we conclude that the observed spillover effects on enrollment and graduation are most likely explained by changes in the decision to apply to a four-year college. This result is well in line with the findings of Altmejd et al. (2022)

and Barrios-Fernández (2022), and they confirm that there are students with the potential to succeed in higher education who for some reason are not applying to it.

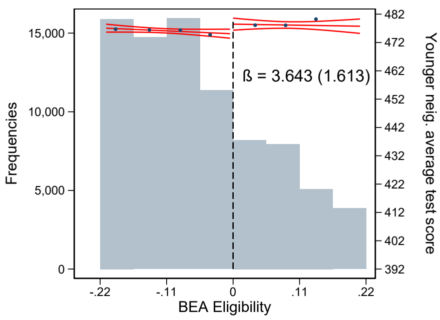
Figure 8: Effects of older neigbor's BEA eligibility on the younger neighbors' educational performance and PSU take-up



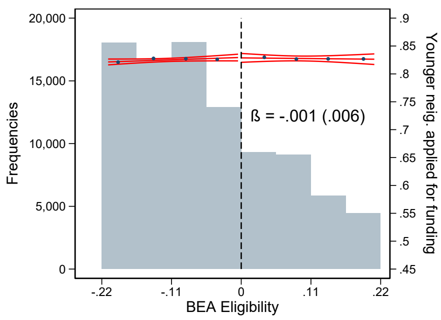
(a) High school GPA



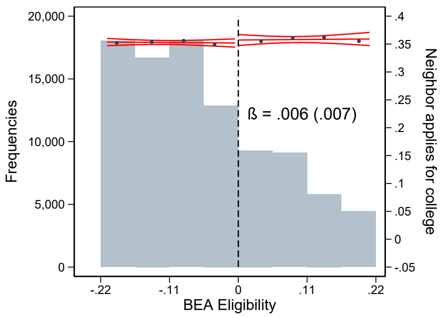
(b) Pr. of taking the admission exam



(c) Test score (conditional on take-up)



(d) Pr. of apply to funding



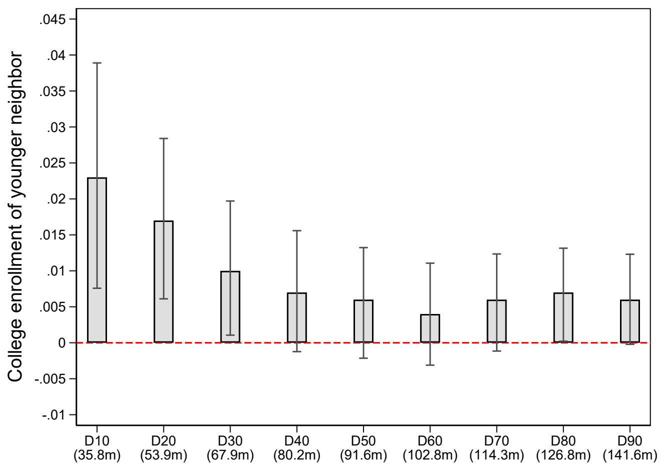
(e) Pr. of apply to college

Notes: The Figure shows RDD estimates of older-neighbor BEA eligibility status on younger's neighbors educational performance. Panel (a) presents effects on GPA across high school years. Panel (b) shows BEA effects on taking college admission test. Panel (c) presents effects on college admission test score, conditional on take-up and panel (e) show the probability of aply to college. In Panels (b) and (c), we show the OLS estimate of equation (1) and its standard error in parenthesis (clustered at the school level).

Finally, in Figure 9 we study how neighbor spillovers evolve with distance. If our results are really driven by social interactions, we would expect the effects to be stronger among neighbors who live closer to each other and who are therefore more likely to interact. Figure 9 shows that the effects quickly decline with distance. For this exercise, we use a slightly different sample of neighbors. This sample includes the ten closest neighbors of students in the BEA-eligibility margin and groups them in distance deciles. Thus, while neighbors in the first decile live on average at 35.8 meters from a student near the BEA eligibility cutoff, students in the tenth decile live on average at 141.6 meters from a student near the BEA eligibility cutoff.

To study how the effects evolve with distance, we estimate our main specification independently in ten samples defined by these distance categories. Each distance category "d" accumulates the sample of neighbors associated with distance belonging to the d decile. The figure shows that effects are indeed larger for the closest neighbors. Moreover, estimated impacts smoothly decrease when adding close neighbors who live farther away. In line with Barrios-Fernández (2022), we find that geographic proximity is key for neighbors' effects to arise.

Figure 9: BEA effects on neighbors across relative distance between peers



Notes: In this figure, we depict RDD-based spillover effects across peers' proxy of closeness. Specifically, we estimate the effects of a close neighbor's eligibility status on college enrollment across deciles of geographic distance. In each category, we accumulate the sample of neighbors according to the individual's decile of the older neighbor (potential BEA beneficiary). We show RDD estimate sin bars with the corresponding 95% CIs.

6 Conclusions

The educational trajectories of students from different social groups differ in important ways. Students from disadvantaged backgrounds are less likely to attend higher education and those who attend higher education are less likely to enroll in selective colleges. This is true even when looking at talented individuals who would likely benefit from a college education. These differences are costly, as they significantly impact individuals' future earnings, and in the aggregate, can affect economic growth and inequality.

Recent studies have shown that affirmative action and special admission programs are effective in expanding access to higher education for underrepresented groups. And although there is some debate on whether these programs could lead to mismatch, there is vast evidence showing that talented students from disadvantaged backgrounds benefit from them.

This paper studies a program designed to increase access to selective colleges for students from disadvantaged backgrounds who complete high school in the top 10% of their class. In line with previous studies, we find that this program significantly increases 4-year college enrollment and graduation for their beneficiaries.

In addition, we show that the program also benefits close neighbors and younger siblings of its direct beneficiaries. This result is important as it confirms that social spillovers can amplify the effects of programs designed to expand college access. Indeed, the indirect effects that we document on enrollment and graduation are larger than the direct effects. Thus, it is important to incorporate these social spillovers into the cost-benefit analysis of these programs. Further research is required to understand whether these social spillovers can be used to improve the effectiveness and efficiency of programs tackling inequality in postsecondary education trajectories.

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